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(54) **ADVERTISEMENT RENDERING**

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(58) **Field of Classification Search**
CPC G06Q 30/0207–0277
USPC 705/14, 319
See application file for complete search history.

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(57)   **ABSTRACT**

A system selects a set of advertisement media associated with a product. A set of persistent advertisement media from the set of advertisement media is identified based on one or more tests. A Gaussian Bayesian (GB) network based on the set of advertisement media. A net persistence rate for each of the set of persistent advertisement media is determined based on the GB network. a competitor factor associated with another vendor of the product is computed based on one or more marketing parameters associated with the another vendor. A predicted sales (PS) value associated with each of the set of persistent advertisement media is determined. A persistent advertisement medium is selected in real time based on corresponding PS value. An advertisement is rendered on the selected persistent advertisement medium in real time for marketing the product.
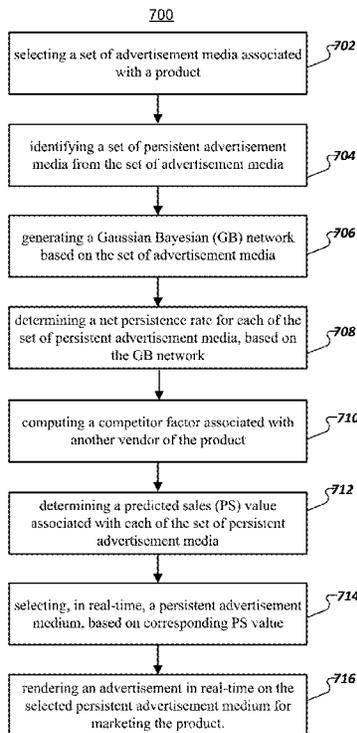
9 Claims, 9 Drawing Sheets

700

<u>100</u>

Figure 1(a)

130

Advertiser network 132

System 102

DSP 136

Data Management Platform 138

Ad Network 140-1

Ad Server 142-1

Publisher Network 134

SSP 144

Data Broker 146

Ad Network 140-2

Ad Server 142-2

Figure 1(b)

Data Processor 118

Data Aggregator 200

Transformation Rules Applicator 204

Regression Applicator 206

Figure 2

Graph 1

rf

Figure 3(a)

Graph 2

Figure 3(b)

Persistent Media selector <u>120</u>

Unit Root tester
<u>300</u>

Cointegration
tester <u>302</u>
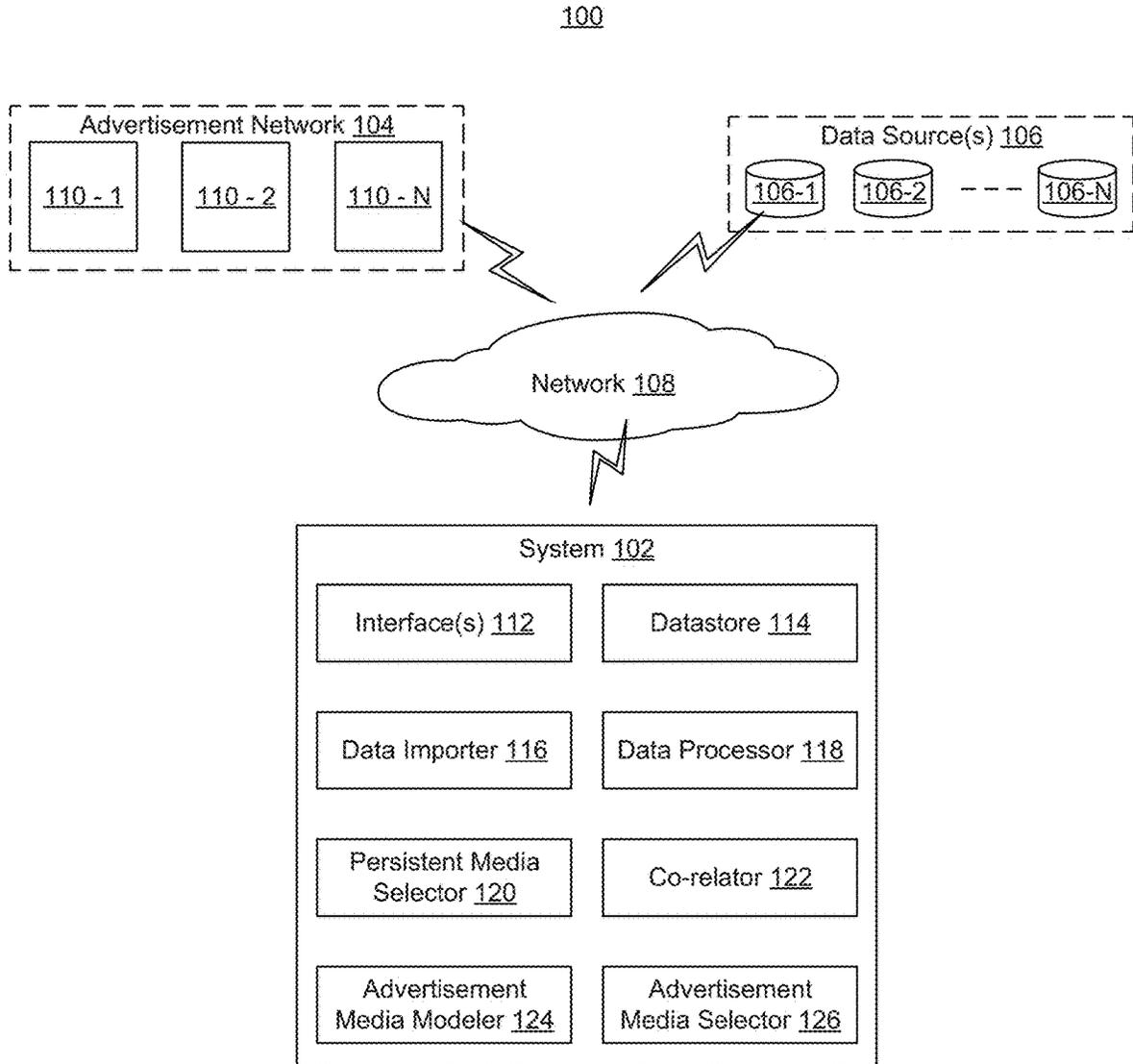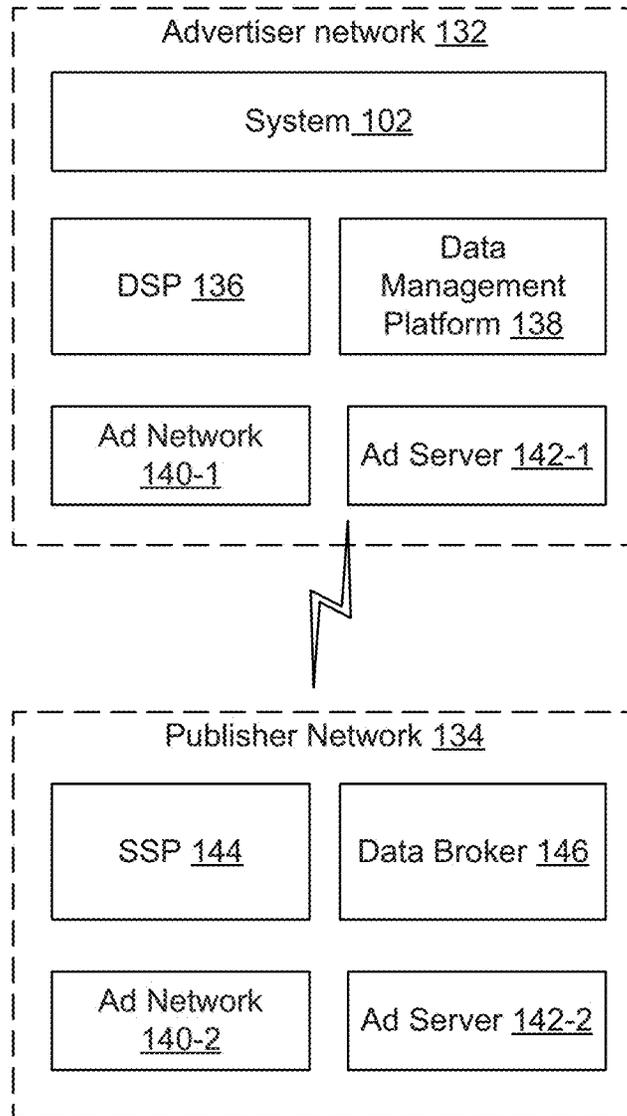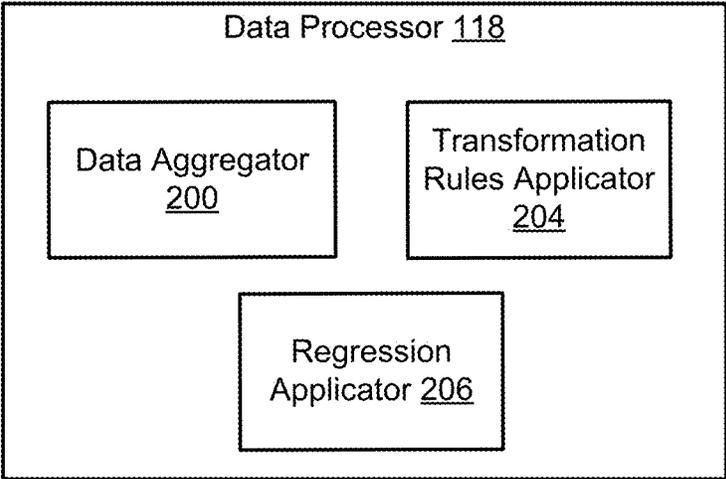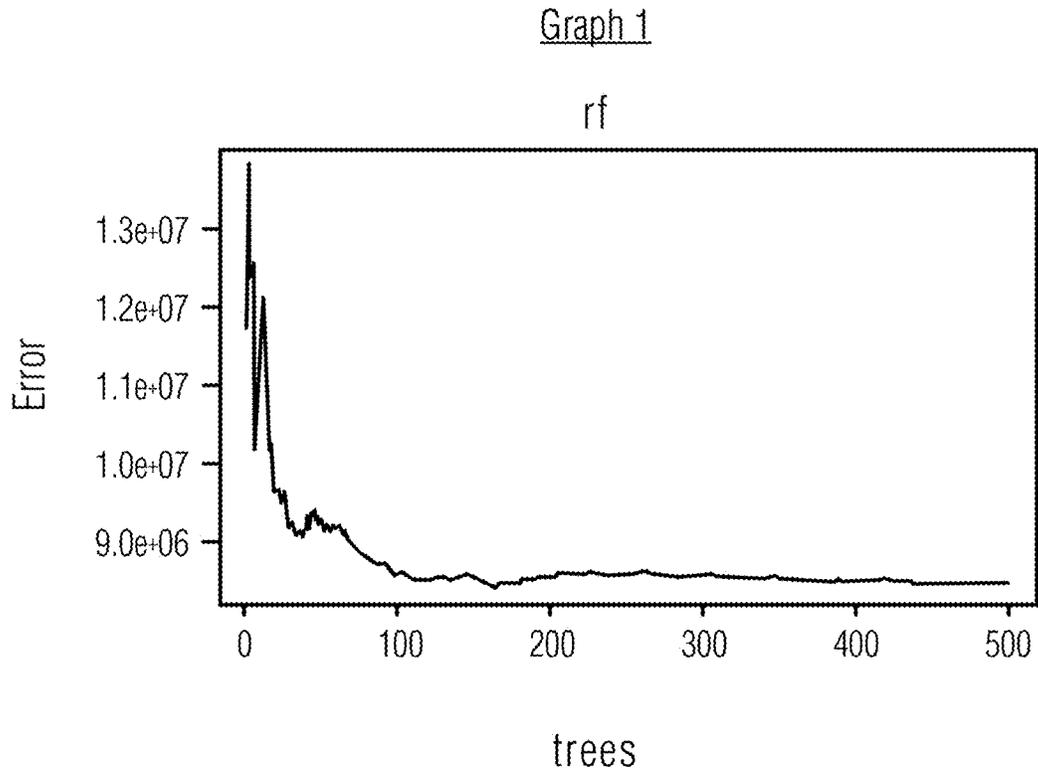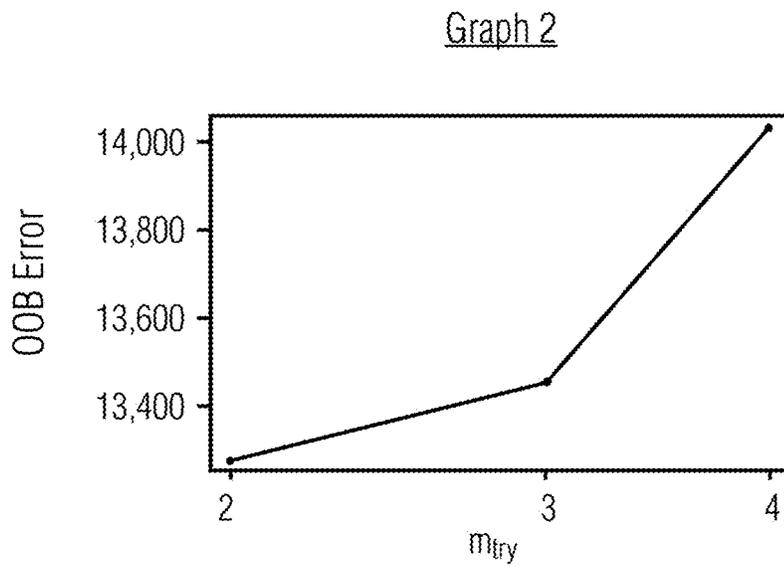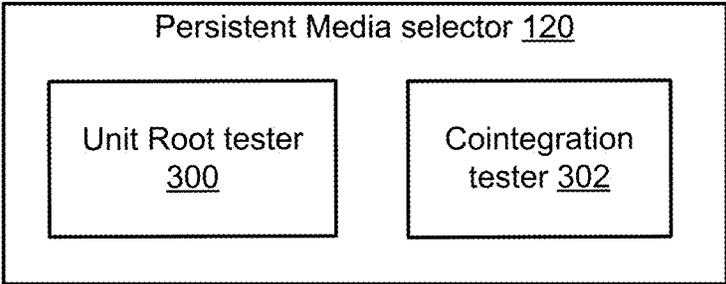
Figure 4

Figure 5

Figure 6

Decay Analysis

◉ % Contribution Realized in 3yrs (with no decay)

◎ % Contribution Realized in 3yrs (with decay)

TV   ONLINE PAID
SEARCH   ONLINE DISPLAY   LOCAL
NEWSPAPER   PRINT

Figure 7(a)

Long Term Decay

Figure 7(b)

700

selecting a set of advertisement media associated with a product ⟋702

↓

identifying a set of persistent advertisement media from the set of advertisement media ⟋704

↓

generating a Gaussian Bayesian (GB) network based on the set of advertisement media ⟋706

↓

determining a net persistence rate for each of the set of persistent advertisement media, based on the GB network ⟋708

↓

computing a competitor factor associated with another vendor of the product ⟋710

↓

determining a predicted sales (PS) value associated with each of the set of persistent advertisement media ⟋712

↓

selecting, in real-time, a persistent advertisement medium, based on corresponding PS value ⟋714

↓

rendering an advertisement in real-time on the selected persistent advertisement medium for marketing the product. ⟋716

Figure 8

Figure 9

ADVERTISEMENT RENDERING

PRIORITY

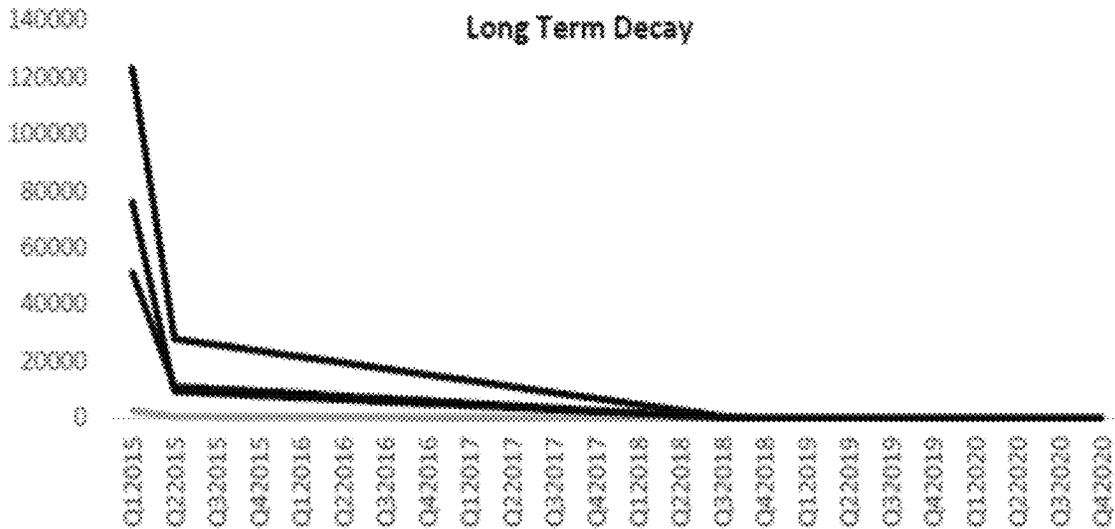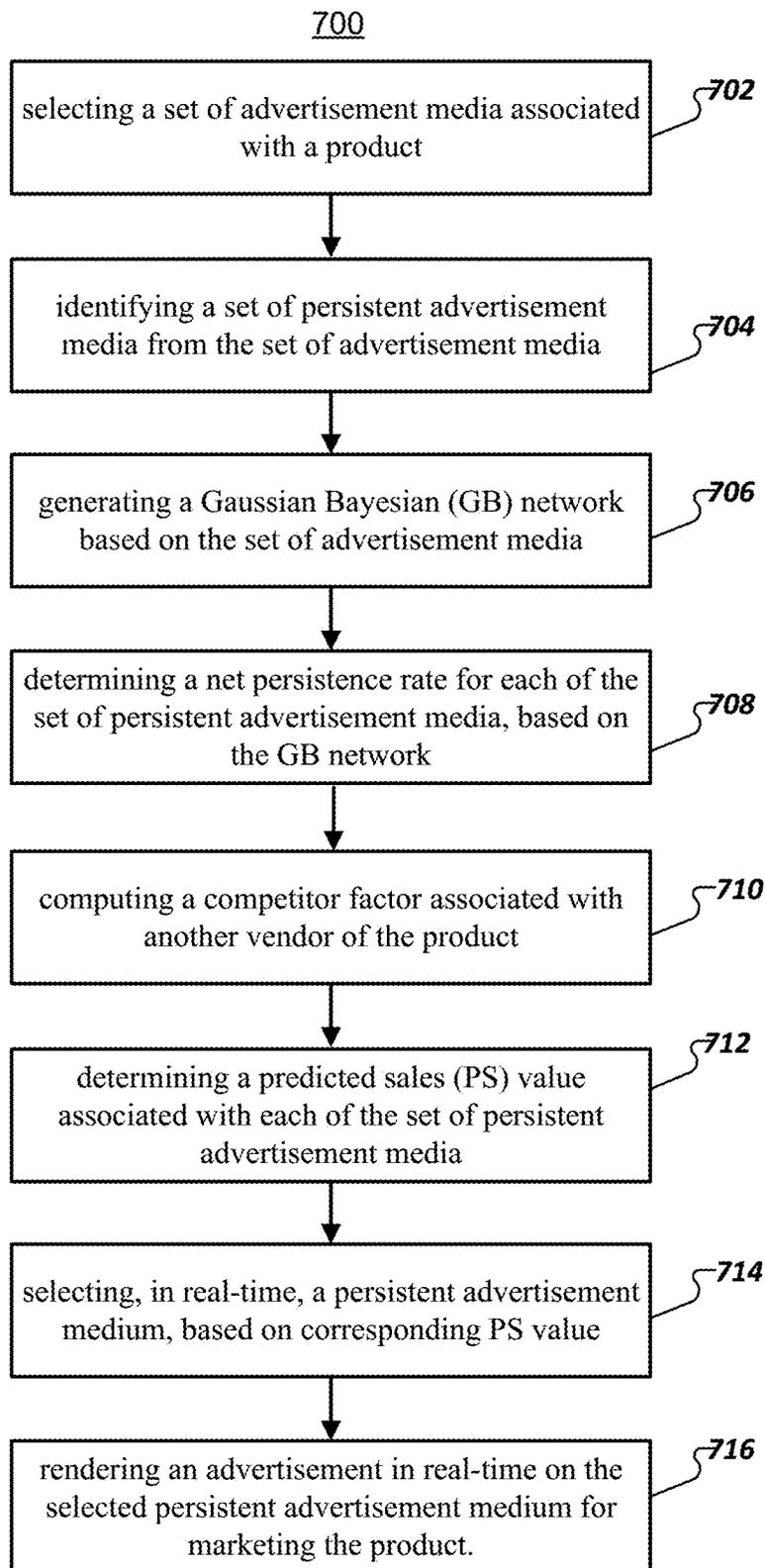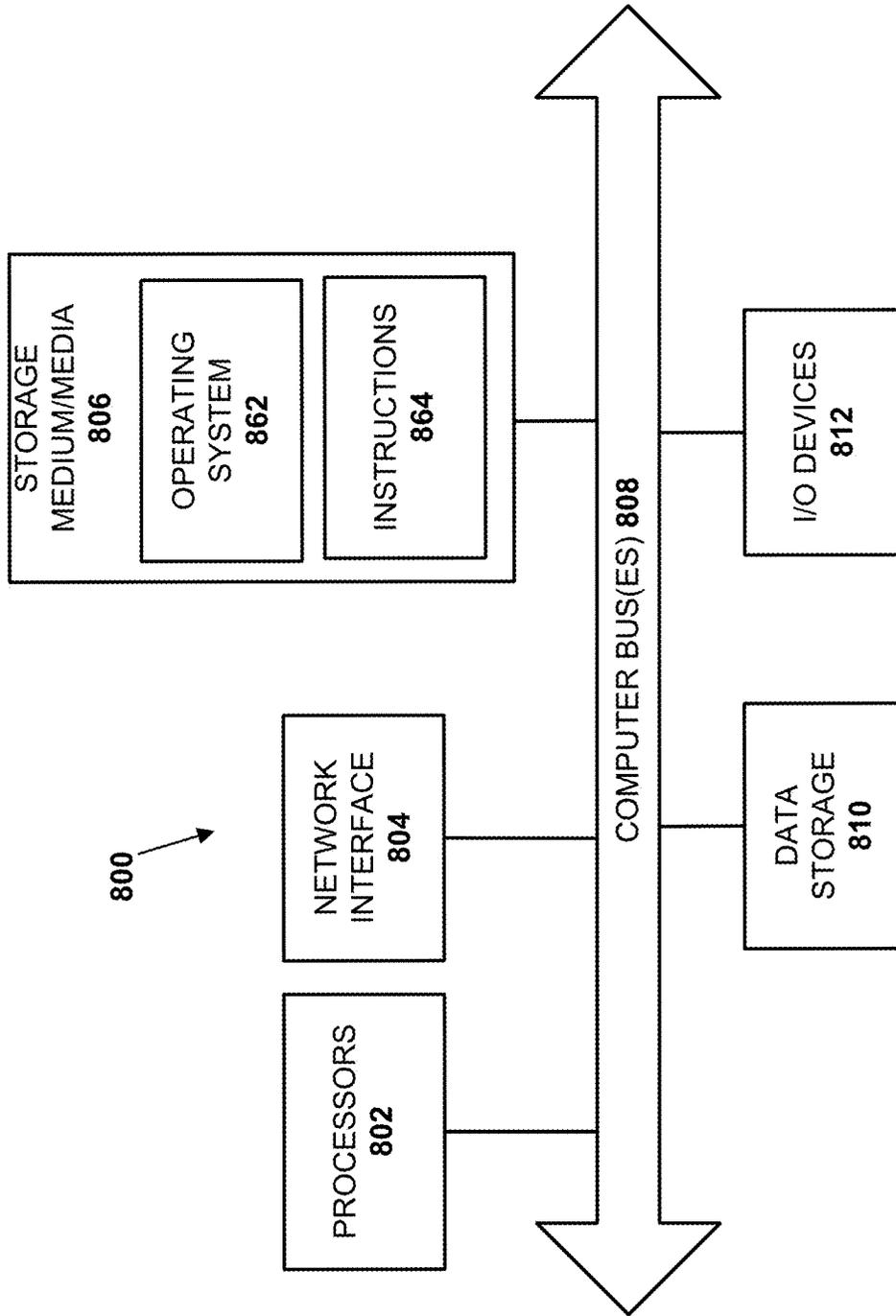The present application claims priority under 35 U.S.C. 119(a)-(d) to Indian patent application number 201711033446, having a filing date of Sep. 21, 2017, the disclosure of which is hereby incorporated by reference in its entirety.

BACKGROUND

Marketing of a product includes advertising the product through various advertisement media, such as, for example, the Internet, newspapers, television commercials, banner advertisements, and commercials on radio. In order to learn the impact of the advertising on the consumers, manufacturers or vendors of the product conduct routine surveys related to the product. Through these surveys, consumer feedback related to the product is gathered, and subsequently analyzed, for example, to learn about the impact of advertising through various advertisement media and to identify the sales generated through each of the advertisement media. Accordingly, the manufacturer or the vendor designs subsequent advertisement strategies for achieving maximum sales.

In a typical approach of learning about the impact of advertising through various advertisement media, consumer surveys may be conducted. However, such surveys do not represent an accurate dataset related to the product and may result in incorrect analysis of the sales of the product. Also, the analysis mostly project short term impacts of advertising through various advertisement media and in that, the approach is limited. Furthermore, colleting raw data for the analysis in the form of consumer surveys is a tedious task in itself.

Some of the other technical limitations in currently used systems include not having the ability to analyze the long term impact of advertisement campaigns and the impact of competitors' advertisement campaigns on the sales of products. In addition, such systems do not include the capability to modify ad campaigns and particular advertisements themselves in real time based on the analysis of the long term impact of advertisement campaigns and the impact of competitors' advertisement campaigns.

BRIEF DESCRIPTION OF DRAWINGS

The embodiments are described in detail in the following description with reference to the following figures. The figures illustrate examples of the embodiments.

FIG. 1(a) illustrates an example network implementation of a system, in accordance with the present disclosure.

FIG. 1(b) illustrates an example network implementation of a system, in accordance with the present disclosure.

FIG. 2 illustrates an example of a data processor, in accordance with the present disclosure.

FIGS. 3(a) and 3(b) illustrate an implementation of the random forest regression technique, in accordance with the present disclosure.

FIG. 4 illustrates an example of a persistent media selector, in accordance with the present disclosure.

FIG. 5 illustrates an example of a Gaussian Bayesian network, in accordance with the present disclosure.

FIG. 6 illustrates an example of a advertisement media selector, in accordance with the present disclosure.

FIGS. 7(a) and 7(b) illustrates example graphs, in accordance with the present disclosure.

FIG. 8 illustrates an example of a method for rendering advertisement, in accordance with the present disclosure.

FIG. 9 illustrates an example of a computer platform, in accordance with the present disclosure.

DETAILED DESCRIPTION

For simplicity and illustrative purposes, the embodiments of the disclosure are described by referring mainly to examples thereof. Also, numerous specific details are set forth in order to provide a thorough understanding of the embodiments. It will be apparent however, to one of ordinary skill in the art, that the embodiments may be practiced without limitation to one or more of these specific details. In some instances, well known methods and structures have not been described in detail so as not to unnecessarily obscure the description of the present disclosure. In the present disclosure, the term "includes" means includes but not limited thereto, the term "including" means including but not limited thereto. The term "based on" means based at least in part on. In addition, the terms "a" and "an" are intended to denote at least one of a particular element.

Manufacturers or vendors of a product run advertisement campaigns of their products through various advertisement media, such as, for example, newspapers, television, radio, banner ads, and the like. It may be important for the manufacturers/vendors to learn about the success of the advertisement campaigns. That is, manufacturers/vendors may want to know if the advertisement campaign are impacting the sales of the product and if so, by how much. A measure of the effectiveness of an advertisement campaign may include determining the impact of each individual advertisement media used as part of the advertisement campaign.

According to aspects of the present subject matter, marketing and advertisement data associated with a product may be obtained, and subsequently analyzed using a system implementing machine learning algorithms. During the analysis, factors such as brand decay and indirect contribution of advertisement media, and competitor marketing factor may be determined for identifying persistent advertisement media having long term impact on the sales of the product. The brand decay may be understood as the effect of advertisement in driving sales of a product post removal of the advertisement from a particular advertisement medium. The indirect contribution of an advertisement medium may be understood as the indirect contribution of the advertisement medium in driving the sales of the product. For instance, National TV advertisement may lead to an online search for the product, thereby indirectly affecting sales of the product. The competitor factor may be understood as impact on sales due to advertisement and marketing done by competitor vendors.

For each of the persistent advertisement media, predicted sales (PS) value or return on investment (ROI) value may be computed and accordingly, steps for optimizing advertisement and marketing of the product may be performed. For instance, based on the PS value or ROI value, one of the persistent advertisement media may be selected for real time rendering of an advertisement related to the product.

Furthermore, according to the present disclosure, the marketing and advertisement data is collected digitally. This may lead to the collected dataset to be sufficiently large and thus accurate. Additionally, the, collection of such a dataset is less tedious and less cumbersome as opposed to manual

collection of data through means of consumer surveys. Furthermore, the present disclosure provides a scalable approach of integrating with existing advertisement networks, thereby facilitating real time rendering of the advertisement based on the analysis of the advertisement data.

FIG. 1(a) illustrates a network environment 100 implementing a system 102 for rendering advertisements, in accordance with an example embodiment of the present subject matter. In an example, the system 102 may be implemented by a vendor or a manufacturer of a product seeking to learn the impact of advertising done on various advertisement media, such as, for example, Internet, print, television, and radio. System 102 may also be implemented by a third party that analyzes the impact of advertisement campaigns on the sales of products.

The system 102, in an example, is connected to an advertisement network 104 and a plurality of data sources 106, through a network 108. The system 102 may be implemented in one or more computing devices, such as a server, a workstation computer, a personal computer, a tablet, a laptop, a desktop computer, a smartphone, and the like. The advertisement network 104 may be understood as a network comprising a plurality of advertisement media, such as, for example, print, television, radio, Internet searches (paid and unpaid), Internet advertisements, email advertisements, banner advertisements, advertisements on vehicles, and the like, depicted by, 110-1, 110-2, . . . , 110-N. The data sources 106 includes at least one of Public data, Social media data, and audience data, represented by 106-1, 106-2, . . . , 106-N. Example public data may include weather data, national holiday calendar data, unemployment data, data associated with enterprises and manufacturers, media advertisement data, and the like. Example Social media data may include, tweets, posts, article sharing activity, event creation activity, and the like. Example audience data may include information associated with consumers, feedback data received from consumers, and the like.

The network 108 may be a cellular network, a broadband network, a telephonic network, an open network, such as the Internet, or a private network, such as an intranet and/or the extranet, or any combination thereof. In other examples, the network 108 can be any collection of distinct networks operating wholly or partially in conjunction to provide connectivity between the system 102, the advertisement network 104, and the data source(s) 106. Furthermore, the network 108 may include and/or support one or more networks, such as, but are not limited to, one or more of WiMax, a Local Area Network (LAN), Wireless Local Area Network (WLAN), a Personal area network (PAN), a Campus area network (CAN), a Metropolitan area network (MAN), a Wide area network (WAN), a Wireless wide area network (WWAN), or any broadband network, and may be further enabled with technologies such as, by way of example, Global System for Mobile Communications (GSM), Personal Communications Service (PCS), Bluetooth, WiFi, Fixed Wireless Data, 2G, 2.5G, 3G, 4G, IMT-Advanced, pre-4G, LTE Advanced, mobile WiMax, WiMax 2, WirelessMAN-Advanced networks, enhanced data rates for GSM evolution (EDGE), General packet radio service (GPRS), enhanced GPRS, iBurst, UMTS, HSPDA, HSUPA, HSPA, UMTS-TDD, 1×RTT, EV-DO, messaging protocols such as, TCP/IP, SMS, MMS, extensible messaging and presence protocol (XMPP), real time messaging protocol (RTMP), instant messaging and presence protocol (IMPP), instant messaging, USSD, IRC, or any other wireless data networks, broadband networks, or messaging protocols.

The system 102, in an example, includes an interface(s) 112, datastore 114, a data importer 116, a data processor 118, a persistent media selector 120, a co-relator 122, an advertisement media selector 124, and an advertisement media selector 126. The interface(s) 112 may include one or more of audio, video, input/output interfaces. The datastore 114 may be a storage medium for storing data, processes, predefined rules, algorithms, software, operational instructions, internal data, external data, and other product related data, such as sales data, advertisement data comprising advertisements related to the product, and the like.

In operation, a data importer 116 of the system 102 may obtain product data related to the product from the data sources 106 over the network 108. In another example, the data importer 116 may obtain the product data from an external storage device, for example, a pen drive, connected to the system 102 through the interface(s) 112. The product data may include data indicative of advertisement and sales of the product. For instance, the product data may include at least one of a gross rating point (GRP) associated with different advertisement media used for marketing the product. In an example, the data importer 116 may store the product data in the datastore 114 for further analysis.

Once the product data is obtained, a data processor 118 of the system 102 may identify a plurality of advertisement media associated with the product based on the product data. In other words, the product data is analyzed and advertisement media related to advertisement and sales of the product are identified. Examples of the advertisement media may include, but are not limited to, newspaper ads, social media posts and ads, print ads, e-mail advertisement broadcasts, radio, television, advertisement banners, advertisements posted on web pages, advertisement through paid searches, and the like.

Once the plurality of advertisement media is identified, the data processor 118 applies a regression technique on the identified plurality of advertisement media for selecting a set of advertisement media. In an example, the set of advertisement media may include those advertisement media which significantly impacts the sales of the product.

Based on the set of advertisement media, a persistent media selector 120 of the system 102 identifies a set of persistent advertisement media and a co-relator 122 of the system 102 generates a Gaussian Bayesian (GB) network. The set of persistent advertisement media includes advertisement media having long term equilibrium relationship with sales of the product. In other words, the set of persistent advertisement media includes those advertisement media which have a long term impact on the sales of the product.

The GB network generated is indicative of the relationships (represented by arcs) between the set of advertisement media and the sales of the product. The relationship between an advertisement medium and the sales of the product may be a direct one, or an indirect one. Also, at an instant, the advertisement medium may have more than one relationship with the sales. As an example of direct relationship, the national TV may influence the sales of a product directly through an advertisement aired on the National TV. As an example of indirect relationship, an advertisement done on the National TV may prompt a user to investigate further about the product through online searching. The online search may result in a sale of the product and thus, in this manner, the National TV may drive the sale of the product indirectly as well.

For generating the GB network, the co-relator 122 obtains the set of advertisement media and predefined lists stored in the datastore 114. The predefined lists may include a white

list and a black list defining relationships between the advertisement media and the sales. For instance, a relationship from National TV to Sales is logical, and is thus included in the white list. Whereas, a relationship from Sales to National TV is not logically correct, and is thus included in the black list. Thus, based on the white list and the black list, the co-relator **122** defines the relationships between the advertisement media and the sales. Thereafter, the co-relator **122** may run a hill climbing algorithm and stepwise regression for addition/deletion of advertisement media may be performed. Thus, a plurality of GB networks may be generated. In an example, the co-relator **122** may select a GB network having the lowest Bayesian Information Criterion (BIC) value. An exemplary GB network is illustrated in FIG. **5**, described below.

Once the set of persistent variables is identified and the GB network is generated, the advertisement media modeler **124** determines a predictive sales (PS) value for each of the persistent advertisement media. The PS value of an advertisement medium may be indicative of a number of the products predicted to be sold by a further time period as a result of advertisement/marketing through the advertisement medium. For determining the PS value, the advertisement media modeler **124** computes a net persistence rate for each of the set of persistent advertisement media and a competitor factor associated with another vendor of the product.

For computing the net persistence rate associated with a persistent advertisement medium, the advertisement media modeler **124** at first computes short-term contribution of each of the set of advertisement media. using equation 1 and 2 provided below.

$$\text{Sales}_{(t)} = a_0 + a_1 \text{Sales}_{(t-1)} + a_2 \text{TV}_{(t)} + a_3 \Delta \text{TV}_{(t)} + a_4 \text{Search}_{(t)} + a_5 \text{Print}_{(t)} + a_6 \Delta \text{Print}_{(t)} + \theta Z_{(t)} + a_7 \text{TV} \text{Attack} + a_8 \text{CompPaidSearch} + \epsilon_{(t)} \quad (1)$$

$$\text{Search}_{(t)} = b_0 + b_1 \text{Search}_{(t-1)} + b_2 \text{TV}_{(t)} + b_3 \Delta \text{TV}_{(t)} + b_4 \text{Print}_{(t)} + b_5 \Delta \text{Print}_{(t)} + \theta Z_{(t)} + \epsilon_{(t)} \quad (2)$$

where,

$S_{(t)}$ and $S_{(t-1)}$ are sales at time t and t−1;

a_o is the intercept, that is, sales when no advertising/ marketing is done;

b_o is the search intercept, i.e., sales through search when no advertising/marketing is done;

a_n is the level coefficient for different advertisement media for direct path (n=1 to x);

b_n is the level coefficient for different advertisement media for indirect path (n=1 to x);

Δ is the change in the sales from time t−1 to t (also referred to as difference coefficient); and

ϵ_t is the error coefficient.

Equation 1 represents a direct path, i.e., direct relation between the sales and the advertisement media. Equation 2 represents an indirect path between the search advertisement medium and the sales. As can be seen, the sales through search is driven by other advertisement media as well.

Based on the equation 1 and 2, and advertisement data (Example table 1) below, the advertisement media modeler **124** generates both, direct and indirect, short-term contribution for each of the advertisement media depicted below in example tables 2 and 3, respectively.

EXAMPLE TABLE 1

Variable	Dependent	Estimate	StdErr	tValue
Sales$_{(t-1)}$ (a$_1$)	Sales	0.64	0.03	20.12
National TV (a$_2$)	Sales	112.29	34.44	3.26

EXAMPLE TABLE 1-continued

Variable	Dependent	Estimate	StdErr	tValue
ΔNational TV (a$_3$)	Sales	57.28	23.27	2.46
Search (a$_4$)	Sales	0.10	0.05	2.25
Print (a$_5$)	Sales	854.91	525.86	1.63
ΔPrint (a$_6$)	Sales	270.43	122.25	2.21
TV Attack(a$_7$)	Sales	−90.43	18.54	−4.88
IPhone	Sales	2220.92	1162.97	1.91
Comp Paid Search(a$_8$)	Sales	−4.31	3.38	−1.4
Search$_{(t-1)}$ (b$_1$)	Search	0.81	0.03	28.22
National TV (b$_2$)	Search	72.71	21.27	3.42
ΔNational TV (b$_3$)	Search	25.71	23.27	6.42
Print (b$_4$)	Search	842.09	541.44	1.56
ΔPrint (b$_5$)	Search	384.09	241.44	1.32

EXAMPLE TABLE 2

Direct Path	
Driver	R52 Contribution %
Comp Paid Search	−2.99%
IPhone	4.20%
Search	7.08%
National TV	6.92%
Print	4.08%
TV Attack	−0.42%

EXAMPLE TABLE 3

Indirect Path: Search		
Search	R52 Contribution %	R52 Net Contribution %
National TV	10.58%	0.75%
Print	6.24%	0.44%

where R52 is the recent 52 weeks contribution.

The direct short term contribution of an advertisement medium, for example, National TV is calculated by adding the coefficients related thereto in the direct path (a2 and a3). The indirect short-term contribution of National TV may be computed by adding the co-efficients related thereto in the indirect path (b2 and b3). In an example, for an advertisement medium, such as, search, which includes indirect sales from other advertisement media, such as National TV and print, the share of the National TV and print may be deducted from the total sales of Search. Also, the indirect sales of the National TV is then added to the total sales of National TV.

In an example, the advertisement media modeler **124** may utilize a short term decay (example table 4) for determining the net short term contribution for the advertisement media (example table 5). In an example, the short term decay is based on the adstock and the power associated with the advertisement medium.

EXAMPLE TABLE 4

Short Term decay			
Description	Adstock	Power	Months of Complete decay
National TV	0.6	0.7	9
Print	0.4	0.7	5
Search	0.4	0.8	4

EXAMPLE TABLE 5

Short Term R52 Total Net Contribution	
Variables	R52 Net Contri %
National TV	8.71%
Search	6.63%
Print	5.88%
IPHONE	4.20%
TV ATTACK	-0.42%
COMP PAID SEARCH	-2.99%

On computing the net-short term contribution for each of the persistent advertisement media, the advertisement media modeler **124** computes a persistence rate for each of the persistent advertisement media using equation 3 provided below.

$$\text{Persistence Rate (persistent advertisement medium)} = \qquad (3)$$

$$\frac{\text{Difference\_Coeff}}{\text{Difference\_Coeff} + \text{Level\_Coeff}}$$

Based on equation 3 above, the advertisement media modeler **124** may compute a direct path persistence rate (example table 6) and an indirect path persistence rate (example table 7) for each of the persistent advertisement media.

EXAMPLE TABLE 6

Direct Path Persistence Rate Calculation			
Variable	Level Coeff	Difference Coeff	Persistence Rate
National TV	112.29	57.28	34%
Print	854.91	270.43	24%

EXAMPLE TABLE 7

Indirect Path: Search Persistence Rate Calculation			
Variable	Level_Coeff	Difference_Coeff	Persistence_Rate
National TV	72.71	25.71	26%

Upon computing the direct path persistence rate and the indirect path persistence rate, the advertisement media modeler **124** may compute a net persistence rate (Example table 8) for each of the advertisement media using equation 4 below.

$$\text{Net Persistence Rate (persistent advertisement medium)} = \qquad (4)$$

$$\frac{\text{Short Term Net Contribution}}{\text{Contribution due to Persistence}}$$

For instance, for computing the net persistence rate of National television, the advertisement media modeler **124** may determine the net short term contribution due to national television and may compute the contribution due to persistence related to the national television (both direct and indirect). Accordingly, the advertisement media modeler **124** may determine the net persistence of the national TV (example table 8).

EXAMPLE TABLE 8

Variable	Short Term R52 Net Contribution	Contribution Due to Persistence	Net_Persistence_Rate
National TV	1,009,982	383,880	38%
Print	427,636	56,077	13%

Once the net persistence rate is determined, the advertisement media modeler **124** may compute the competitor factor associated with the another vendor. In an example, the competitor factor may be based on a first competitor model and a second competitor model. The first competitor model may be a media mix model, i.e., the first model may take into account the advertisement/marketing activity of the vendor, and may be determined using equation 5 provided below.

$$\text{Sales} = b_0 + b_1 \text{Media} + b_2 \text{Competitor} + b_3 \text{Controls} + \varepsilon \qquad (5)$$

Here, Media denotes the marketing and advertising done by the vendor, and control denotes the other factor such as season sales, demographic factors, and the like. For instance, a sale season may increase the sales of the product or the location of a user may drive sales of a particular product. For instance, sales of a cold drink may be more in a warmer climate region as opposed to a cold climate region. Further, b_2 indicates the sales of the another vendor. Together, the variables of the equation 5 may be referred to as marketing variables, in an example. Based on equation 5 above, the media mix model may be determined (example table 9). In an example, the first competitor model may indicate the impact on the sales of the vendor due to the another vendor on a quarterly basis as depicted below in example table 9.

EXAMPLE TABLE 9

		Media Mix Model	
Year_Qtr	Sales	Contribution	% Contribution
2014_Qtr2	336509	-13753	-4.10%
2014_Qtr3	349629	-15776	-4.50%
2014_Qtr4	440588	-15945	-3.60%
2015_Qtr1	336954	-14282	-4.20%

The second competitor model may be a model independent of the marketing and advertisement activity of the vendor, and may be referred to as the competitor only model. The competitor only model in an example, may be computed using equation 6 provided below.

$$\text{Sales} = b_0 + b_1 \text{Competitor} + b_2 \text{Controls} + \varepsilon \qquad (6)$$

As can be seen, the sales are independent of the marketing or advertising activity of the vendor. An example table 10 depicting the quarterly sales based on the competitor only model is provided below.

EXAMPLE TABLE 10

		Competitor Model	
Year_Qtr	Sales	Contribution	% Contribution
2014_Qtr2	336509	−35236	−10.50%
2014_Qtr3	349629	−36022	−10.30%
2014_Qtr4	440588	−36810	−8.40%
2015_Qtr1	336954	−39850	−11.80%

In an example, the advertisement media modeler **124** may perform a summation (Example Table 11) of the quarterly contribution of the another vendor from both the competitor only model and the media mix model.

EXAMPLE TABLE 11

Year_Qtr	% Net Contri
2014_Qtr2	−6.4%
2014_Qtr3	−5.8%
2014_Qtr4	−4.7%
2015_Qtr1	−7.6%

Subsequently, the advertisement media modeler **124** may determine an average of all the quarters to determine the competitor factor. In the aforementioned example tables, the competitor factor is −6.1%. The competitor factor of −6.1 takes into account the marketing/advertising activity of the vendor. As may be understood, the impact of the marketing/advertising done by the vendor, herein also referred to as brand equity, would persist for a time period and, therefore, an actual value (−6.1%) of the competitor factor would not be attained instantaneously. Considering the brand equity, the advertisement media modeler **124**, in an example, may determine a time period after which the competitor factor attains its full value. An example case is described below with the help of example table 12.

EXAMPLE TABLE 12

Driver	Adstock	No Of weeks taken to reach 6%	weeks	Competitor Impact
National TV	0.6	10	week 1	−6.10%
National TV	0.6		week 2	−3.66%
National TV	0.6			
National TV	0.6			

EXAMPLE TABLE 12-continued

Driver	Adstock	No Of weeks taken to reach 6%	weeks	Competitor Impact
National TV	0.6		week 10	−0.06%
Print	0.4	7	week 1	−6.10%
Print	0.4		week 2	−2.44%
Print	0.4			
Print	0.4			
Print	0.4		week 7	−0.02%

In an example, the advertisement media modeler **124** computes the time period after which the competitor factor would reach its full value based on the adstock value associated with the persistent advertisement medium. Thus, as illustrated above in the example table 12, for computing the time period for National TV, corresponding adstock factor of 0.6 is considered. At first, the advertisement media modeler **124** determines the adstock in percent form. Thus, the adstock factor of 0.6 is converted to 60%. Subsequently, the advertisement media modeler **124** iteratively computes an adstock percent value of the competitor factor, i.e., 60 percent of 6.1%, till a time period the competitor factor becomes almost zero. Thus, as can be seen above, by week 10, the competitor factor nears zero value. Thus, the advertisement media modeler **124** determines 10 weeks to be the time period at which the competitor factor would attain its full value. As may be gathered, the adstock is indicative of the impact of an advertisement medium on the consumers. Thus, factoring in the adstock accounts for the brand equity of the vendor. By performing this process for all the advertisement media, the advertisement media modeler **124** takes into account the brand equity achieved due to the persistent advertisement media.

As mentioned above, the advertisement media modeler **124** computes the PS value based on the net persistent rate associated with each of the set of persistent advertisement media and the competitor factor. In addition to the aforementioned factors, the advertisement media modeler **124**, in an example, utilizes sales data associated with the product. The sales data may be understood as data indicative of a number of the products sold during a defined time period due to the marketing done through an advertisement medium. The computation of the PS value is described in conjunction with example table 13 and example table 14, provided below.

EXAMPLE TABLE 13

Variable	Persistence Rate	R52_Net_Contribution	Number of weeks	Weekly Average Contribution	Weekly Persistence Contribution
National TV	38%	1,009,982	52	19,423	7,381
Print	13%	427,636	52	8,224	1,069

Example table 13, illustrated above, includes one or more persistent advertisement media, their corresponding persistence rates, their corresponding Net contribution to sales for a defined time period, their weekly contribution to sales, and weekly contribution due to persistence.

EXAMPLE TABLE 14

Variable	Net Persistence Rate	R52 Contri	Year1	Year2	Year3	Contri Realized in 3 Years	% Contri Realized in 3 years with decay	% Contri Realized in 3 years (If No Decay)
National TV	38%	1,009,982	327,054	239,216	151,377	717,648	71%	114%
Print	13%	427,636	47,865	35,010	22,154	105,030	25%	39%

Example table 14, illustrated above, includes one or more persistent advertisement media, their corresponding persistence rates, their corresponding Net contribution to sales for a defined time period, their annual sales due to persistence for subsequent years, their sales for a further period (3 years herein) with persistence (decay) and without persistence.

For computing the PS value associated with an advertisement medium (National TV), the advertisement media modeler **124** at first, computes a unit persistence contribution (Weekly persistence contribution (7381), table 13) associated with the advertisement medium based on a net contribution (R52_Net_Contribution (1,009,982), table 13) associated with the advertisement medium, the defined time period (52 weeks, table 13, and the net persistence rate (38%, table 13).

Thereafter, the advertisement media modeler **124** computes at least one variable decay value based on the competitor factor and the adstock value associated with the advertisement medium. By computing the decay values, the advertisement media modeler **124** takes into account the brand equity of the vendor. As described earlier with reference to example table 12, the competitor factor is achieved after some time period, first time period hereinafter. Thus, as may be understood, the further time period for which the PS value is computed may include the first time period, and a second time period.

As an example, referring to the example table 12, one or more variable decay values till 10th week may be computed. For instance, the variable decay value for 2nd week would be competitor factor for second week minus competitor factor for first week. Likewise, the decay factor for each week running upto the 10th week may be calculated. An example table 15 depicting the variable decay value is provided below.

EXAMPLE TABLE 15

Week Number	Initial Contribution	Variable Decay %	Net Competitor Effect Eroding Sales	Final Contribution
National TV				
1	7,381	−0.06%	−5	7,376
2	7,376	−0.10%	−8	7,369
—	—	—	—	—
—	—	—	—	—
10	6,734	−6.10%	−411	6,324

On computing the variable decay values, the advertisement media modeler **124** computes at least one updated unit persistence contribution (Final contribution (7376), table 15) done during the first time period based on the unit persistence contribution and the variable decay value. In aforementioned example, to determine the contribution of sales for the first time period (10 weeks), the advertisement media

modeler **124** may add the updated unit persistence contributions (final contribution from week 1 till week 10) for the first time period.

As may be understood, at the end of first time period, the competitor factor is at its full value (−6.1%). Thus, using the full value of the competitor factor, the advertisement media modeler **124** in an example, computes at least one further updated unit persistence contribution during the second time period (from 11th week till end of third year). Thereafter, based on the contributions made during the first time period and the second time period, the advertisement media modeler **124** computes the PS value (Contri Realized in 3 Years (717,648), table 14) associated with the persistent advertisement medium. In an example, the advertisement media modeler **124** may determine the PS value in a percentage form (71%, table 14).

Thus, the advertisement media modeler **124** computes the PS value associated with all the persistent advertisement media. The computed PS values may be stored in the datastore **114** as sales prediction data.

In an example, a advertisement media selector **126** of the system **102** may access the sales prediction data to identify a persistent advertisement media whose predicted sales is maximum. Upon identifying the persistent advertisement medium, the advertisement media selector **126** may select, in real-time, the persistent advertisement medium for marketing the product. Subsequently, the advertisement media selector **126** may render, in real-time, an advertisement related to the product on the persistent advertisement medium. For instance, the advertisement media selector **126** may render the advertisement on the persistent advertisement medium **110-1**. In an example, prior to rendering, the advertisement media selector **106** may modify the advertisement in real time based on the PS value. For instance, if the persistent advertisement medium has high PS values, the advertisement media selector **126** may modify the advertisement to remove excess graphics and advertisement. As a result, the data storage and computing overheads associated with the advertisement are reduced and yet acceptable sales of the product may be achieved.

As a part of rendering, the advertisement media selector **126** may also determine, in real-time, an advertisement platform, through which the advertisement may be rendered to the consumers. For instance, the advertisement media selector **126** may identify print as the persistent advertisement medium, and may further determine newspaper as the advertisement platform. The advertisement platform, in an example, may be determined based on the sales data.

As may be gathered from the foregoing description, the system **102** takes into account long run effects of advertisement media to determine predicted sales value or on in other words, a true return on investment (ROI) related to advertisements run on the advertisement media. Based on the determined PS value or ROI value, the system **102**, in an

example, may render advertisements in the marketplace in near real time, such as, for example, weekly, or monthly.

FIG. 1(b) illustrates a network environment **130** implementing the system **102** for optimizing advertisement rendering in a market place. The network environment **130** includes an advertiser network **132** and an a publisher network **134**. The advertiser network **132** includes the system **102**, a demand-side platform (DSP) **136**, a data management platform **138**, an ad network **140-1**, and an ad server **142-1**. The publisher network **134** includes a selling-side platform (SSP) **144**, a data broker **146**, an ad-network **140-2**, and an ad server **142-2**.

The publisher network **134**, in an example, may be understood as a network of publishers, such as, for example, digital publishers, online publishers, offline publishers, rendering advertisement services to manufacturers, vendors, importers, exporters, enterprises, and the like. The advertiser network **132**, in an example, may be understood as a network of advertisers (manufacturers, vendors, importers, exporters, enterprises, and the like) seeking to render advertisements through advertisement media provided by the publisher network **134**. Although not shown in the figure, either one or both, the advertiser network **132** and the publisher network **134** may include a right to bid (RTB) client for facilitating bidding related to purchase/sale of advertisement rights related to various advertisement media.

As can be seen from the figure, an advertiser may implement the system **102** for optimizing advertisement rendering on various advertisement media. In an example, the system **102** may determine the PS value or the ROI value related to the advertisement media in real time, that is, monthly, weekly, or every fortnight. Based on the determined PS value or ROI value, the system **102** may generate an expenditure model. The expenditure model may include information related to the plurality of advertisement media and corresponding PS or ROI value. Based on the expenditure model, in an example, the system **102** may generate instructions for bidding for advertisement rights for one or more advertisement media from the plurality of advertisement media. Once the instructions are generated, the system **102** may transmit the bids to the DSP **136** and the RTB client, for placing the bids with the SSP **144**. Accordingly, the system **102** facilitates the purchase of advertisement rights in real time, such as, for example, on a monthly or weekly basis.

As an example, the system **102** may facilitate purchase of advertisement rights for digital advertisement media, such as, for example, the Internet. Furthermore, in addition to selecting the advertisement medium, say, a website, the system **102**, facilitates in determining an advertisement platform, say, for example, a standard banner or a video ad. In another example, the system **102** may facilitate the purchasing of the advertisement rights for offline advertisement media, such as, for example, National TV. In said example, the system **102** may facilitate in determining the time slots and other attributes, such as sponsored or non-sponsored advertisements for effective rendering of advertisements. Furthermore, for digital advertisement media like paid searches, the system **102** may facilitate the selection of keywords based on the analysis performed by the system.

FIG. **2** illustrates a block diagram depicting components of the data processor **118**. The data processor **118** includes a data aggregator **200**, a transformation rules applicator **202**, and a regression applicator **206**. As mentioned above in the description of FIG. **1**, the data processor **118** identifies the plurality of advertisement media and selects the set of advertisement media.

In operation, the data aggregator **200** processes the product data, i.e., performs at least one of a cleaning, ordering, and grouping operation on the product data. As a result, the product data, post the aforementioned operations, include data which is relevant for analyzing the sales and advertisement of the product, and is relatively noise free.

Post processing of the product data, the transformation rules applicator **204** applies one or more transformation rules, such as, for example, an adstock transformation rule and a power transformation rule, on the product data. Based on the adstock transformation rule, an adstock value of an advertisement media may be obtained. Similarly, based on the power transformation rule, a power value of an advertisement media may be obtained. The adstock value of an advertisement media may be understood as a value depicting the prolonged or lagged effect of marketing on purchase behavior of a consumer. The power related to an advertisement media may be understood as a power function computed based on the corresponding GRP value associated with the advertisement media. The power of the advertisement may be computed to account for diminishing sales returns. In an example, for each advertisement media, the transformation rules applicator **204** may compute an adstock value and a power value based on the GRP value associated with the advertisement media. based on a GRP value of each advertisement media. In an example, the transformation rules applicator **204** may perform iterative application of the transformation rules to obtain a plurality of combinations of advertisement media and sales. In an example, the transformation rules are applied based on a user input received through the interface **112**. The user input, in an example, may include definitions related to the advertisement media. Further, in an example, the user input may include instructions or commands to select/modify/delete the aforementioned combinations. The user input, in an example, may be based on interactions between the different advertisement media.

Once the plurality of advertisement media is identified, the regression engine **206** applies the regression technique for identifying the set of advertisement media. In an example, if the advertisement media are in a continuous form, the regression applicator **206** may apply a Lasso regression technique. The lasso regression technique selects the significant advertisement media from the plurality of advertisement media based on model fit statistics, such as, for example, akaike's information criterion (AIC), R-squared (R^2), and the like. As an example, in the lasso regression technique, the regression applicator **206**, at first, computes estimates and subsequently reduces the errors related thereto based on error reduction equation given below.

$$\hat{\beta}=Min\ \Sigma_i(y_i-\beta_i x_i)^2,\ constraint=\Sigma_i P|\beta_i|\leq t \qquad \text{Error Reduction Equation}$$

Here y_i=actual data, $\beta_i x_i$=predicted data, β_i=estimate, and t=variable to control shrinkage of parameters.

Based on the aforementioned equation, the regression applicator **206** may reject any estimate that may be greater than 't'. As a result, over-fitting problems are averted. The estimates that are selected, that is the sales figures corresponding to the advertisement media which are selected are then added iteratively in conformance to AIC criterion given below.

$$AIC=-2(log\text{-}likelihood)+2K \qquad \text{AIC criterion}$$

where, K=Number of advertisement media plus intercept and Log-likelihood: Measure of model fit. In an example, the set of advertisement media are selected based on a model

which is robust and has minimum AIC. That is, the advertisement media are added till the cumulative AIC value goes on decreasing. An example model 1 is depicted below.

Example Model 1

Advertisement media	AIC
Intercept	6750.381
National TV	6457.961
Search	6451.254
Competitive Search	6442.372
TV_Attack	6429.96
Radio	6419.703
Print	6419.414
Brand Awareness	6407.491*
Newspaper	6409.315

In the example model 1 illustrated above, the advertisement media till brand awareness are selected as the cumulative AIC value goes on decreasing. Post brand awareness, the AIC value starts increasing again.

In another example, when the advertisement media are in discrete form, the regression applicator 206 may use a random forest regression technique. The random forest regression technique is an ensemble learning technique for reducing errors. In the random forest regression technique, a plurality of decision trees are generated and an average output of individual trees is computed. In said technique, the sales are taken as dependent variables and the advertisement media are taken as nodes. The error rate is monitored and the number of trees is selected when the reduction in error is constant, for instance, as depicted in graph 1 shown in FIG. 3(a).

As may be observed, the regression applicator 206 may select the number of trees (ntree) to be equal to 100 as the reduction in error becomes constant. Subsequently, the trees may be split and the number of advertisement media selected at each split, hereinafter "mtry", may be determined based on minimum out of bag (OOB) error. The OOB error may be understood as the mean prediction error on each training sample x_i, using only the trees that did not have x_i in their bootstrap sample. Continuing with the above example, based on the graph 2 shown in FIG. 3(b), the value of mtry may be determined to be three.

Subsequently, the regression applicator 206 computes prediction error, for example, mean squared error (MSE), for each tree. The MSE may be computed by taking a square of difference between the actual data and the predicted data. In one example, the difference is averaged over all the trees. Accordingly, the MSE in terms of percentage is obtained for each of the advertisement media, as depicted below in example table 16.

EXAMPLE TABLE 16

Advertisement medium	MSE
National_TV	5.26012
Radio	4.684573
Search	4.500345
Print	3.835894
TV_Attack	2.829506
Comp_Paid_Search	2.588429

In an example, the regression applicator 206 may select the regression technique based on a user input received through the interface 112.

FIG. 4 illustrates a block diagram depicting components of the persistent media selector 120. The persistent media selector includes a unit root tester 300 and a cointegration tester 302. As mentioned above, the persistent media selector 120 identifies the set of persistent advertisement media from the set of advertisement media.

In operation, for each of the set of advertisement media, the unit root tester 300 may determine whether the advertisement medium is stationary or evolving. In a case where the advertisement medium is stationary, the unit root tester 300 may discard the advertisement medium. On the other hand, if the advertisement medium is evolving, the unit root test medium 300 may identify the advertisement medium to be a persistent advertisement medium. That is, it is inferred that the advertisement media would have a long term or persistent effect on the sales of the product. For determining whether the advertisement medium is stationary or evolving, the unit root tester 300 performs a dickey fuller test and computes an observed value (Tau1), a critical value (Tau2), a p-value, and an alpha value for each of the advertisement media. Subsequently, an advertisement medium whose corresponding p-value is less than the corresponding alpha value is deemed to be stationary and discarded. For instance, in the example table 17, given below, the p-value of Radio is less than apha value for radio.

EXAMPLE TABLE 17

	National TV	Search	Print	Radio
Tau1 (Observed value)	−2.87	−3.12	−1.45	−5.14
Tau1 (Critical value)	−3.45	−3.45	−3.45	−3.45
p-value	0.21	0.1	0.06	0.01
Alpha value	0.05	0.05	0.05	0.05
Inference	Non-Stationary	Non-Stationary	Non-Stationary	Stationary

Thus, the Radio is deemed to be stationary and non-evolving. Whereas, as observed, National TV, Search, and print are deemed to be non-stationary, i.e., evolving.

The non-stationary advertisement media are subsequently fed as input to the cointegration tester 302. For each of the non-stationary advertisement media, the cointegration tester 302 ascertains whether a long term equilibrium exists between the advertisement medium and sales of the product, using equation 1 provided below.

$$Sales_t = A + BTV_t \tag{1}$$

Using the equation 1, a regression is run between the advertisement medium, sample results of which are provided below in example table 18.

EXAMPLE TABLE 18

Variable	Coefficient	Std_error	T-stat	P-value
Intercept (A)	−0.390957	0.097112	−4.026	0.00008
National_TV (B)	0.821951	0.0117602	69.893	<0.00001

The sample Table 18 illustrated above indicates regression results for National TV.

Post regression, the cointegration tester 302 calculates residuals for the advertisement media and determines whether the residuals are stationary or not. In a case where

the residuals are stationary, the advertisement medium is deemed to be cointegrated with the sales and is included in the set of persistent advertisement media. On the other hand, if the residual is non-stationary, it is determined that the advertisement media and the sales are not cointegrated and the advertisement media is not included in the set of persistent advertisement media.

FIG. **5** illustrates a screenshot of an exemplary GB network, in accordance with the present subject matter. As can be seen in the figure, relationships between the advertisement media and sales may be direct, indirect, or both. For instance, National TV has both, direct and indirect, relationship with the sales. On the other hand, TV attack has only direct relationship with the sales.

FIG. **6** illustrates a block diagram depicting components of the advertisement media selector **126**. The advertisement media selector **126** includes a graph generator **500**, a media selector **502**, and a renderer **504**. The graph generator **500**, in an example, generates one or more graphs for displaying to a vendor. The graphs, in an example include the a timeline based predicted sales decay of the product. Exemplary graphs are depicted in FIGS. **7**(a) and **7** (b).

Based on the graphs, the vendor may select the persistent advertisement medium, in an example. In another example, the media selector **502** may select automatically select the persistent advertisement medium having the highest corresponding PS value. Subsequent to the selection, the media selector **502** may select the advertisement to be rendered and the advertisement platform. Thereafter, the renderer **504** may render the advertisement on the persistent advertisement medium.

FIGS. **7**(a) and **7**(b) illustrate sample graphs generated by the graph generator **500**. FIG. **7**(a) illustrates a sample graph depicting predicted sales value (with and without decay) for a plurality of advertisement media for a defined period of three years. FIG. **7**(b) illustrates a quarterly breakup of predicted sales through a plurality of advertisement media for a predefined period of five years.

FIG. **8** shows a flowchart **700** that details one example of advertisement rendering. The method begins at **702** wherein a set of advertisement associated with a product are selected. The set of advertisement media may include those advertisement media which are significantly related to the sales of the product. In an example, the selection may be done using one of a lasso regression technique or a random forest technique.

At **704**, a set of persistent advertisement media is identified from the set of advertisement media. The set persistent advertisement media includes advertisement media which have Long term impact on the sales of the product. In an example, a unit root test, followed by a cointegration test may be performed for identifying the set of persistent advertisement media.

At **706**, a Gaussian Bayesian (GB) network is generated based on the set of advertisement media. The GB network is indicative of relationships between the set of advertisement media and the sales of the product. The relationships may be either direct or indirect and an advertisement medium may have both the relationships with the sales.

At **708**, a net persistence rate for each of the set of persistent advertisement media is determined based on the GB network. The net persistence rate is indicative of the sales generated due to persistence of the advertisement media and may be determined in the manner as described above.

At **710**, a competitor factor associated with another vendor of the product is computed. In an example, both, media

mix competitor model and competitor only model may be used for computing the competitor factor.

At **712**, a predicted sales (PS) value associated with each of the persistent advertisement media is determined. The PS value of an advertisement medium is indicative of a predicted sale of the product for a further time period when the product advertised through the persistent advertisement medium. The PS value is computed in a manner as described above.

At **714**, a persistent advertisement medium is selected in real time based on the corresponding PS value. In an example, the persistent advertisement medium with the highest PS value is selected. In an example, the selection may be one of automatic or user selected.

At **716**, an advertisement corresponding to the product is rendered in real time on the selected persistent advertisement medium for marketing the product. In an example, an advertisement platform may too be selected prior to rendering the advertisement. For instance, for print, newspaper may be selected.

FIG. **9** illustrates a computer system **800** that may be used to implement the system **102**. The computer system **800** may include additional components not shown and that some of the components described may be removed and/or modified. The computer system **800** may be a server or the system **80** may be implemented in a distributed computing system on a plurality of servers. Each server may include the components of the computer system **800**.

The computer system **800** includes processor(s) **802**, such as a central processing unit, ASIC or other type of processing circuit, input/output devices **812**, such as a display, mouse keyboard, etc., a network interface **804**, such as a Local Area Network (LAN), a wireless 802.11x LAN, a 3G or 4G mobile WAN or a WiMax WAN, and a computer-readable medium **806**. Each of these components may be operatively coupled to a bus **808**. The computer readable medium **806** may be any suitable medium which participates in providing instructions to the processor(s) **802** for execution. For example, the computer readable medium **806** may be non-transitory or non-volatile medium, such as a magnetic disk or solid-state non-volatile memory or volatile medium such as RAM. The instructions or modules stored on the computer readable medium **806** may include machine readable instructions **864** executed by the processor(s) **802** to perform the methods and functions of the system **102**.

The system **102** may be implemented as software stored on a non-transitory computer readable medium and executed by one or more processors. For example, the computer readable medium **806** may store an operating system **862**, such as MAC OS, MS WINDOWS, UNIX, or LINUX, and the like for the system **102**. The operating system **862** may be multi-user, multiprocessing, multitasking, multithreading, real-time and the like. For example, during runtime, the operating system **862** is running and the code for the system **102** is executed by the processor(s) **802**.

The computer system **800** may include a data storage **810**, which may include non-volatile data storage. The data storage **810** stores any data used by the system **102**. The data storage **810** may be used to store the datastore **114** and may be hosted by separate database servers.

The network interface **804** connects the computer system **800** to internal systems for example, via a LAN. Also, the network interface **804** may connect the computer system **800** to the Internet. For example, the computer system **800** may connect to web browsers and other external applications and systems via the network interface **804**.

What has been described and illustrated herein are examples of the disclosure along with some variations. The terms, descriptions and figures used herein are set forth by way of illustration only and are not meant as limitations. Many variations are possible within the scope of the disclosure, which is intended to be defined by the following claims—and their equivalents—in which all terms are meant in their broadest reasonable sense unless otherwise indicated.

We claim:

1. A method for rendering an advertisement on an advertisement medium for marketing of a product of a vendor, the method comprising:

digitally collecting product data indicative of advertisement and sales related to the product;

determining a plurality of advertisement media associated with the product based on the digitally collected product data and one or more transformation rules; and

analyzing the determined plurality of advertisement media to select a set of advertisement media associated with the product based on a regression technique;

identifying a set of persistent advertisement media from the set of advertisement media based on one or more tests, wherein the set of persistent advertisement media comprises the advertisement media having long term equilibrium relationship with sales of the product;

generating a Gaussian Bayesian (GB) network based on the set of advertisement media, wherein the GB network is indicative of at least one of a direct relationship and an indirect relationship between the set of advertisement media and the sales of the product;

computing a short term contribution for each of the set of persistent advertisement media based on sales data associated with the advertisement medium, the sales data being indicative of a number of products sold during a defined time period due to marketing done through the advertisement medium;

computing a net short term contribution for each of the set of persistent advertisement media based on the short term contribution of the corresponding advertisement media and a short term decay, wherein the short term decay is based on an adstock associated with the corresponding advertisement media;

computing a persistence rate for each of the persistence advertisement media based on a level value of the corresponding advertisement media and a difference value in sale of the products between the defined time period;

determining a net persistence rate for each of the set of persistent advertisement media, based on the persistence rate of the corresponding advertisement media and the net short term contribution of the corresponding advertisement media;

computing a competitor factor associated with another vendor of the product based on a first competitor model and a second competitor model, the first competitor model being independent of the sales of the product achieved by the vendor, and the second competitor model being dependent of the sales of the product achieved by the vendor;

determining a predicted sales (PS) value associated with each of the set of persistent advertisement media, based on at least the corresponding net persistence rate, sales data associated with the advertisement medium and the competitor factor, wherein the PS value associated with a persistent advertisement medium is indicative of a number of the products predicted to be sold by a further

time period when the product is advertised through the persistent advertisement medium, and wherein the further time period comprises a first time period and a second time period, and wherein the determining the PS value comprises:

computing at least one variable decay value based on the competitor factor and the adstock value associated with the advertisement medium;

computing at least one updated unit persistence contribution during the first time period based on the unit persistence contribution and the variable decay value;

computing at least one further updated unit persistence contribution during the second period based on the at least one updated unit persistence contribution and the competitor factor; and

computing the PS value based on the at least one updated unit persistence contribution during the first time period and the at least one further updated unit persistence contribution during the second time period;

selecting, in real-time, a persistent advertisement medium, from the set of persistent advertisement media, based on the corresponding PS value of the persistent advertisement medium for marketing the product;

when the PS value of the selected persistent advertisement medium is greater than a threshold value, modifying the advertisement in real-time to remove access graphics and streaming via video the modified advertisement in real-time on the selected persistent advertisement medium for marketing the product, wherein the selected persistent advertisement medium includes at least one of a television and a website; and

when the PS value of the selected persistent advertisement medium is less than or equal to the threshold value, streaming via video the advertisement in real-time on the selected persistent advertisement medium for marketing the product, wherein the selected persistent advertisement medium includes at least one of a television and a website.

2. The method as claimed in claim 1, wherein the one or more tests comprise at least one of a unit root test, a dickey fuller test, and a co-integration test.

3. The method as claimed in claim 1, wherein the regression technique is one of a Lasso regression technique and a random forest variable selection technique.

4. The method as claimed in claim 1, further comprising selecting, in real-time, an advertisement platform associated with the advertisement medium for rendering the advertisement related to the product based on a decay rate of the selected persistent advertisement medium for marketing the product.

5. A system for rendering an advertisement on an advertisement medium for marketing of a product of a vendor, the system comprising:

a hardware processor;

a memory to store machine readable instructions for a data processor, a persistent media selector; a co-relator; an advertisement media modeler; an advertisement media selector, and a renderer;

the data processor, wherein the machine readable instructions for the data processor are executable by the hardware processor to:

digitally collect product data indicative of advertisement and sales related to the product;

determine a plurality of advertisement media associated with the digitally collect product based on product data associated with the product and one or more transformation rules; and

analyze the determined plurality of advertisement media to select a set of advertisement media associated with the product based on a regression technique;

the persistent media selector, wherein the machine readable instructions for the persistent media selector are executable by the hardware processor to identify a set of persistent advertisement media from the set of advertisement media based on one or more tests, wherein the set of persistent advertisement media comprises advertisement media having long term equilibrium relationship with sales of the product;

the co-relator, wherein the machine readable instructions for the co-relator are executable by the hardware processor to generate a Gaussian Bayesian (GB) network based on the set of advertisement media, wherein the GB network is indicative of at least one of a direct relationship and an indirect relationship between the set of advertisement media and the sales of the product;

the advertisement media modeler, wherein the machine readable instructions for the advertisement media modeler are executable by the hardware processor to:

compute a short term contribution for each of the set of persistent advertisement media based on sales data associated with the advertisement medium, the sales data being indicative of a number of products sold during a defined time period due to marketing done through the advertisement medium;

compute a net short term contribution for each of the set of persistent advertisement media based on the short term contribution of the corresponding advertisement media and a short term decay, wherein the short term decay is based on an adstock associated with the corresponding advertisement media;

computing a persistence rate for each of the persistence advertisement media based on a level value of the corresponding advertisement media and a difference value in sale of the products between the defined time period;

determine a net persistence rate for each of the set of persistent advertisement media, based on the persistence rate of the corresponding advertisement media and the net short term contribution of the corresponding advertisement media;

compute a competitor factor associated with another vendor of the product based on a first competitor model and a second competitor model, the first competitor model being independent of the sales of the product achieved by the vendor, and the second competitor model being dependent of the sales of the product achieved by the vendor; and

determine a predicted sales (PS) value associated with each of the set of persistent advertisement media, based on at least the corresponding net persistence rate, sales data associated with the advertisement medium and the competitor factor, wherein the PS value associated with a persistent advertisement medium is indicative of a number of the products predicted to be sold by a further time period when the product is advertised through the persistent advertisement medium, and wherein the further time period comprises a first time period and a second

time period, and wherein for the determination of the PS value the advertisement media modeler further is to:

compute at least one variable decay value based on the competitor factor and the adstock value associated with the advertisement medium;

compute at least one updated unit persistence contribution during the first time period based on the unit persistence contribution and the variable decay value;

compute at least one further updated unit persistence contribution during the second period based on the at least one updated unit persistence contribution and the competitor factor; and

compute the PS value based on the at least one updated unit persistence contribution during the first time period and the at least one further updated unit persistence contribution during the second time period; and

the advertisement media selector, wherein the machine readable instructions for the advertisement media selector are executable by the hardware processor to:

select, in real-time, a persistent advertisement medium, from the set of persistent advertisement media, based on the corresponding PS value of the persistent advertisement medium for marketing the product

wherein when the PS value of the selected persistent medium is greater than a threshold value, the advertisement media selector modifies the advertisement in real-time to remove access graphics and the renderer, wherein the machine readable instructions for the renderer are executable by the hardware processor, streams via video the modified advertisement in real-time on the selected persistent advertisement medium for marketing the product, wherein the selected persistent advertisement medium includes at least one of a television and a website; and

when the PS value of the selected persistent medium is less than or equal to the threshold value, the renderer streams via video the advertisement in real-time on the selected persistent advertisement medium for marketing the product, wherein the selected persistent advertisement medium includes at least one of a television and a website.

6. The system as claimed in claim 5, wherein the one or more tests comprise at least one of a unit root test, a dickey fuller test, and a co-integration test.

7. The system as claimed in claim 5, wherein the regression technique is one of a Lasso regression technique and a random forest variable selection technique.

8. The system as claimed in claim 5, wherein the advertisement media selector further is to select, in real-time, an advertisement platform associated with the advertisement medium for rendering the advertisement related to the product based on a decay rate of the selected persistent advertisement medium for marketing the product.

9. A non-transitory computer readable medium including machine readable instructions that are executable by at least one processor to:

digitally collect product data indicative of advertisement and sales related to the product;

determine a plurality of advertisement media associated with the product based on the digitally collected product data and one or more transformation rules; and

analyze the determined plurality of advertisement media to select a set of advertisement media associated with a product based on a regression technique;

identify a set of persistent advertisement media from the set of advertisement media based on one or more tests, wherein the set of persistent advertisement media comprises advertisement media having long term equilibrium relationship with sales of the product;

generate a Gaussian Bayesian (GB) network based on the set of advertisement media, wherein the GB network is indicative of at least one of a direct relationship and an indirect relationship between the set of advertisement media and the sales of the product;

computing a short term contribution for each of the set of persistent advertisement media based on sales data associated with the set of advertisement media, the sales data being indicative of a number of products sold during a defined time period due to marketing done through the set of advertisement media;

computing a net short term contribution for each of the set of persistent advertisement media based on the short term contribution of the corresponding advertisement media and a short term decay, wherein the short term decay is based on an adstock associated with the corresponding advertisement media;

computing a persistence rate for each of the persistence advertisement media based on a level value of the corresponding advertisement media and a difference value in sale of the products between the defined time period;

determine a net persistence rate for each of the set of persistent advertisement media, based on the persistence rate of the corresponding advertisement media and the net short term contribution of the corresponding advertisement media;

compute a competitor factor associated with another vendor of the product based on a first competitor model and a second competitor model, the first competitor model being independent of the sales of the product achieved by the vendor, and the second competitor model being dependent of the sales of the product achieved by the vendor;

determine a predicted sales (PS) value associated with each of the set of persistent advertisement media, based on at least the corresponding net persistence rate and

the competitor factor, wherein the PS value associated with a persistent advertisement medium is indicative of a number of the products predicted to be sold by a further time period when the product is advertised through the persistent advertisement medium, and wherein the further time period comprises a first time period and a second time period, and wherein the determining the PS value comprises:

computing at least one variable decay value based on the competitor factor and the adstock value associated with the advertisement medium;

computing at least one updated unit persistence contribution during the first time period based on the unit persistence contribution and the variable decay value;

computing at least one further updated unit persistence contribution during the second period based on the at least one updated unit persistence contribution and the competitor factor; and

computing the PS value based on the at least one updated unit persistence contribution during the first time period and the at least one further updated unit persistence contribution during the second time period;

select, in real-time, a persistent advertisement medium, from the set of persistent advertisement media, based on the corresponding PS value of the persistent advertisement medium for marketing the product;

when the PS value of the selected persistent advertisement medium is greater than a threshold value, modifying the advertisement in real-time to remove access graphics and streaming via video the modified advertisement in real-time on the selected persistent advertisement medium for marketing the product, wherein the selected persistent advertisement medium includes at least one of a television and a website; and

when the PS value of the selected persistent advertisement medium is less than or equal to the threshold value, streaming via video the advertisement in real-time on the selected persistent advertisement medium for marketing the product, wherein the selected persistent advertisement medium includes at least one of a television and a website.

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